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The primary goal of this research was to develop representations, models, and algorithms for use in Bayesian automated recognition of objects from their images. Despite focused efforts in the area of image understanding in recent years, a fresh look was needed to highlight the progress and the limitations. Our research was focused along the following three broad themes: (i) development of efficient representations of the objects of interest (or their images) using nonlinear manifolds, (ii) development of parametric probability models for capturing object and clutter variability, and (iii) development of algorithms for solving inference problems on nonlinear manifolds that arise in object recognition.

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Bayesian Automated Target Recognition
Final Report for Period: June 15, 1999 to December 31, 2002

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Contents

1 Statement of the Problem Studied

The primary goal of this research was to develop representations, models, and algorithms for use in Bayesian automated recognition of objects from their images. Despite focused efforts in the area of image understanding in recent years, a fresh look was needed to highlight the progress and the limitations. Our research was focused along the following three broad themes: (i) development of efficient representations of the objects of interest (or their images) using nonlinear manifolds, (ii) development of parametric probability models for capturing object and clutter variability, and (iii) development of algorithms for solving inference problems on nonlinear manifolds that arise in object recognition. Next we state the specific problems studied under these three topis.

Although many of these problems are of interest in Army applications, we have mainly utilized public domain data to conduct experiments. Our access to military data was very limited. (One exception is the IR sequences provided by Dr. Richard Sims of AMCOM). We have involved databases such as ORL and FERET for face recognition, COIL for object recognition, Equinox dataset for IR face recognition, our Minolta vivid700 for range image analysis, van Hataren natural image database for image modeling, and so on.

1.1 Representations and Analysis of Image Manifolds

In the space of rectangular arrays of positive numbers, only a small subset has images of interesting scenes. One seeks to isolate and characterize this subset for use in image analysis applications. The main idea is to identify this set as a low-dimensional, differentiable manifold and use its geometry to characterize images. Having defined this manifold, a simplistic probability model can help capture the image variability. We have sought efficient representations of the image manifolds containing images of objects of interest. There are two possible situations: (i) we know the 3D models of the objects of interest beforehand and are interested in estimating the parameters, such as pose, location, state, motion, etc, of their occurrences in a scene, or (ii) we only have some prior observations of the objects' appearances (as images) and want to recognize these objects from their future observations. In the first case, we adopt tools from deformable template theory and denote occurrence variables as elements of groups which act on the object template (e.g. pose is modeled by the rotation and translation group $SE(3)$). In this setup, object recognition becomes a problem in hypothesis selection in presence of nuisance parameters [6]. (Our previous work [4] tackles a related problem of estimating the group elements, and analyzing the estimation performance using error bounds.)

Goal 1 *Treating the problem of object recognition as hypothesis testing in presence of nuisance parameters, how to characterize the performance of Bayesian recognition algorothms?*

The second possibility is that our knowledge of image manifold is restricted to past observations (images) of the objects. Perhaps the easiest technique to approximate the image manifold is to fit a linear subspace through the observations. The fitting criterion will specify the precise subspace that is selected. Many such subspaces have been suggested including PCA, ICA, FDA, non-negative factorization, sparse bases, and their improvements [8, 3, 2, 26, 17, 1, 11]. Simplicity of these linear representations makes them a popular tool in imaging analysis. Two widely used classes of linear representations are dimension reduction subspaces and linear spectral filters. We addressed the following problem:

Goal 2 *In the context of a specific application, such as object recognition or image database retrieval, what are the optimal linear representations of images? Demonstrate the advantages of this approach in a variety of applications using public databases.*

1.2 Probability Models Capturing Object and Clutter Variability

Statistical techniques for image analysis and understanding require efficient and tractable probability models for analyzing the observed images. Given the tremendous variability associated with the imaged objects, detailed (e.g. 3D deformable templates) models are not feasible for "all possible objects". Therefore, one seeks a balance by designing low-level, coarse representations that are tractable and yet capture significant image variation. We have developed a family of tractable, coarse probability models that can form building blocks of a larger image understanding system. Since the image space is very high-dimensional, a direct modeling of the joint probabilities is not possible, even if a large number of observations are provided, and some method for reducing dimensions is required. Motivated by a growing understanding of early human vision, a popular strategy has been to decompose images into their spectral components using a family of bandpass filters. Following that idea, our definition of a probability model on images is through its spectral representation. If certain low-dimensional statistics of these filtered components are found sufficient, then a significant reduction is achieved. It has been shown that spectral components of images have marginals that are: (i) unimodal, (ii) symmetric around the mode, and (iii) are leptokurtic, i.e. their kurtosis are more than that of a Gaussian random variable with the same variance.

Goal 3 *Derive an analytical model that explains and captures this non-Gaussian statistics of the observed images. Demonstrate the use of this model in applications such as texture synthesis, clutter classification, and object recognition.*

1.3 Algorithms for Inferences on Image Manifolds

Many problems in signal and image processing can be efficiently stated and solved on nonlinear manifolds. Here are some examples: subspace tracking in signal processing can be studied as a problem of nonlinear filtering on a Grassmann manifold, estimating pose of a target using images is an estimation problem on the rotation group, finding optimal linear projection of images for retrieval is an optimization problem on Grassmann manifold, analysis of shapes of planar objects is an inference problem on a nonlinear shape manifold, and so on. However, these approaches require dealing with the geometry of nonlinear manifolds, spaces for which the commonly used tools (for representation, optimization, random sampling, and hypothesis testing) are not frequently available.

Goal 4 *Develop mathematical formulations, optimization strategies, statistical procedures, and programming code to study problems of statistical inferences on nonlinear manifolds.*

In particular, the problem of statistical analysis of shapes deserve a separate mention. For analyzing shapes of planar, closed curves, we have proposed differential geometric representations of curves using their direction functions and curvature functions. Shapes are represented as elements of infinite-dimensional spaces and their pairwise differences are quantified using the lengths of geodesics connecting them on these spaces. Our research focused on addressing the following questions:

Goal 5 *How to define and compute geodesic paths on these shape spaces? How to define and compute statistics, such as means and covariances, from probability models on shapes spaces?*

2 Summary of the Most Important Results

In this section we summarize our progress towards these five goals and related areas.

1. **Statistical Modeling of Images & Their Applications**: Seeking probability models for images, we employed a spectral approach where the images are decomposed using bandpass filters, and probability models are imposed on the filter outputs (also called spectral components). We have derived a (two-parameter) family of probability densities [5], named **Bessel K forms**, for modeling the marginal densities of the spectral components, and have demonstrated their fit to the observed histograms for video, infrared, and range images. The density function associated with the linear representations of images is been shown to be [5, 23]: for $p > 0$, $c > 0$,

$$f(x; p, c) = \frac{1}{Z(p, c)} |x|^{p-0.5} K_{(p-0.5)}(\sqrt{\frac{2}{c}}|x|) \ , \quad x \in I\!R \ , \tag{1}$$

where K is the modified Bessel function of third kind and Z is the normalizing constant given by $Z(p, c) = \sqrt{\pi}\Gamma(p)(2c)^{0.5p+0.25}$. The two parameters p and c can be estimated using the equations:

$$\hat{p} = \frac{3}{\mathrm{SK}(I^{(j)}) - 3}, \quad \hat{c} = \frac{\mathrm{SV}(I^{(j)})}{\hat{p}} \ , \tag{2}$$

where SK is the sample kurtosis and SV is the sample variance of the pixel values in $I^{(j)}$. Here, $I^{(j)}$ denotes the image I filtered by the filter $F^{(j)}$. Shown in the top panels of Figure 1 are some images taken from the van Hateren [25] database. The middle panels display their specific filtered forms (or spectral components) for Gabor filters at arbitrarily chosen orientations and scales, and the bottom panels plot the marginal densities. On a log scale, the observed densities (histograms) are plotted in the marked (knotted) lines and the estimated Bessel K forms ($f(x; \hat{p}, \hat{c})$) are plotted in the solid lines. Motivated by object-based models

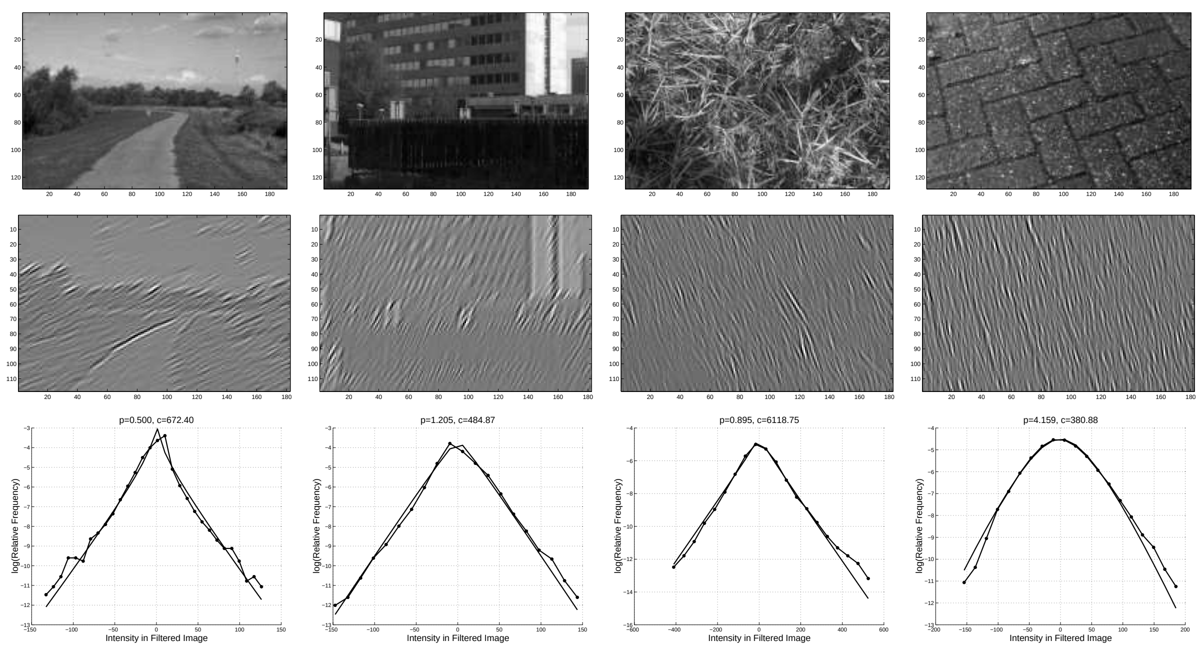


Figure 1: Images (top panels), their Gabor components (middle panels), and the marginal densities (bottom panels). The observed densities are drawn in marked lines and the estimated Bessel K forms are drawn in solid lines.

for image analysis, a relationship between the Bessel parameters and the imaged objects is also established. Using L^2-metric on the set of Bessel K forms, we have proposed a pseudo-metric on the image space for quantifying image similarities/differences. Some applications, including clutter classification and pruning of hypotheses for target recognition, are presented in [23]. This research was performed in collaboration with Prof. Ulf Grenander of Brown University and Prof. Xiuwen Liu of FSU.

We have also presented a survey of the advances made in statistical modeling of images in a recent article [21]. Starting from early Fourier-based techniques to more recent non-Gaussian statistical models for wavelet coefficients of images, we summarize progress in modeling the statistical behavior of images and applications of such models.

2. **Statistical Analysis of Planar Shapes**: For analyzing shapes of planar, closed curves, we have proposed differential geometric representations of curves using their direction functions and curvature functions. Shapes are represented as elements of infinite-dimensional spaces and their pairwise differences are quantified using the lengths of geodesics connecting them on these spaces. We have used a Fourier basis to represent tangents to the shape spaces and then used a gradient-based shooting method to solve for the tangent that connects any two shapes via a geodesic. Using the Surrey fish database, we have demonstrated some applications of this approach: (i) interpolation and extrapolations of shape changes, (ii) clustering and recognition of objects according to their shapes, and (iii) statistical analysis of shapes including computation of intrinsic means and covariances. These results are presented in the papers [10, 9, 20]. As illustration, shown in Figure 2 are two examples of geodesics between shapes on the left and the target shapes on the right. Drawn in between are shapes denoting equally spaced points along the geodesic paths. There are several reasons for finding geodesic paths between shapes. Firstly, the lengths of these geodesics provide a quantification of the differences between any pair of given shapes. Secondly, the shapes along the geodesic paths can be used to interpolate between the shapes, and more interestingly, help define average shapes. Furthermore, this helps in computing statistics from any probability model on such shape spaces.

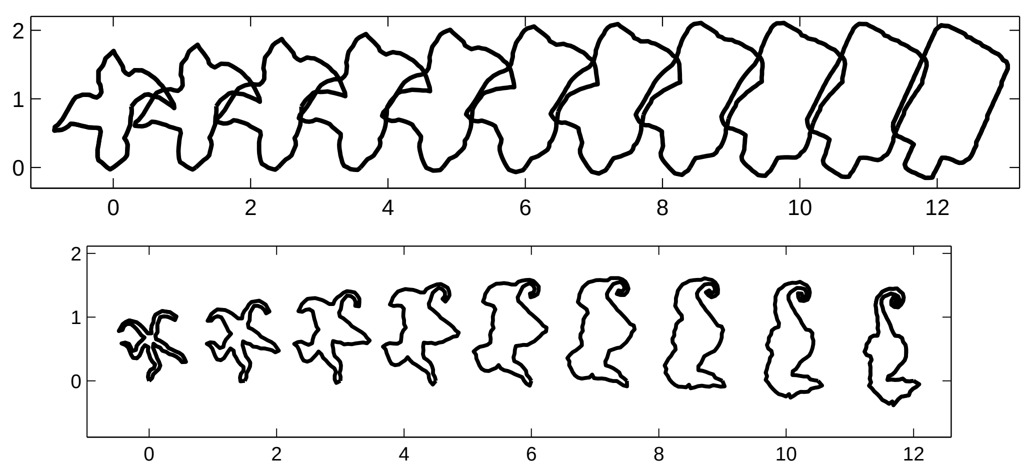


Figure 2: Examples of evolving one shape into another via geodesic paths.

In addition to computing geodesic paths and geodesic lengths for quantifying shape differences, we have also derived a framework for statistical inferences on the nonlinear, infinite-dimensional shape space. Using the notion of Karcher means, we have derived an algorithm for computing mean shapes and shape covariances. Shown in Figure 3 are two examples of computing the Karcher mean shapes: the left four panels show the sample shapes and the rightmost panels display the corresponding mean shapes. More examples have been presented in [10, 9, 20].

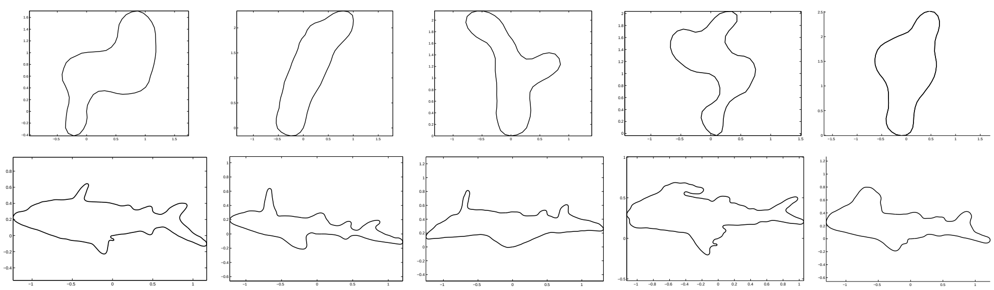


Figure 3: Karcher means (right panels) of the four shapes given in left panels for each row.

The methodology developed for analyzing planar shapes can also be deployed in other applications. Many applications in signal processing, image analysis, and computer vision require tools for "interpolating" between points on some differentiable manifold. As for example, in the problem of recognizing objects in given images, extraction and use of edges/boundaries present in the images play an important role. In case the objects of interest are partially obscured by other objects, the edges are visible only partially, and an important task is to interpolate between the observed edges using information from the observed portions. Let $\alpha\colon [a, b] \to \mathbb{R}^n$ be a smooth curve parametrized by arc length, i.e., satisfying $\|\alpha'(s)\| = 1$, for every s. The *curvature* of α at s is given by $\kappa(s) = \|\alpha''(s)\|$ and the *elastic energy* E of α is defined by $E(\alpha) = \frac{1}{2}\int_a^b \kappa^2(s)ds$. Given the end points and the end directions, we have derived algorithms for finding curves that satisfy the boundary conditions, and have the smallest elastic energy amongst all such curves [16]. Shown in Figure 4 are some examples of using elastic curves in discovering hidden edges of partially obscured objects.

3. **Stochastic Search for Optimal Linear Representations**: Simplicity of linear representations (of images) makes them a popular tool in imaging analysis applications such as object recognition and image classification. Although several linear representations, namely PCA, ICA, and FDA, have frequently been used, these representations are generally far from optimal in terms of actual application performance. We have argued that representations should be chosen with respect to the application and the databases involved. Fixing an application, say object recognition, and assuming that recognition performance is computable for any linear basis (given a classifier and a database), we have proposed a Monte Carlo simulated annealing method that leads to optimal linear representations by maximizing the recognition performance over the space of all subspaces [12, 14, 15, 13]. Let n be the dimension of image space and we are interested in finding an optimal d (with $d << n$) dimensional subspace of $\mathbb{R}^n$ that maximizes the recognition performance in the subspace. Let $\mathcal{G}_{n,d}$ be the Grassmann manifold of all d-dimensional subspaces of $\mathbb{R}^n$ and $F : \mathcal{G}_{n,d} \mapsto \mathbb{R}_+$ denote the recognition performance. Using a Monte Carlo based stochastic search we find $U^* \in \mathcal{G}_{n,d}$ that maximizes F. We have illustrated this method on several popular image databases (of faces, objects, textures, and natural images) and have demonstrated significant improvement over commonly used linear representations. Shown in Figure 5 are some summary results using the ORL

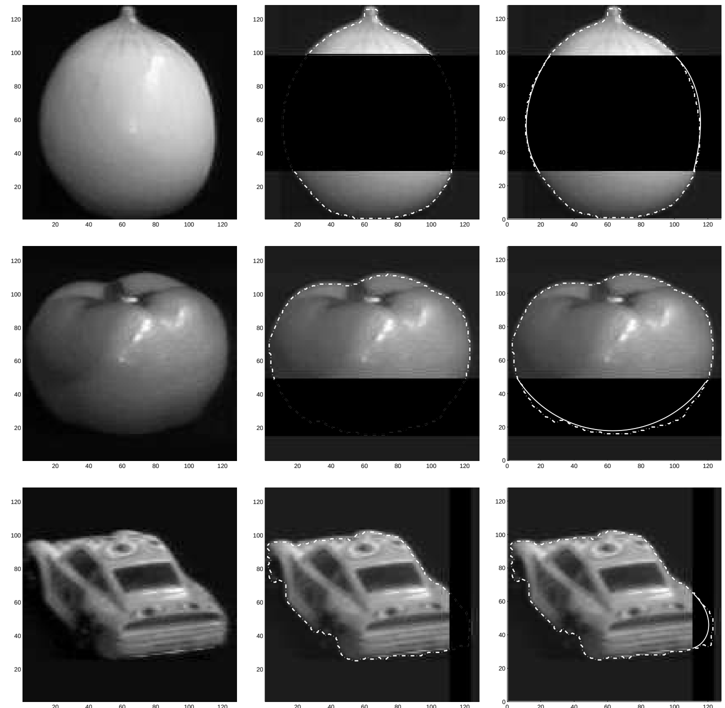


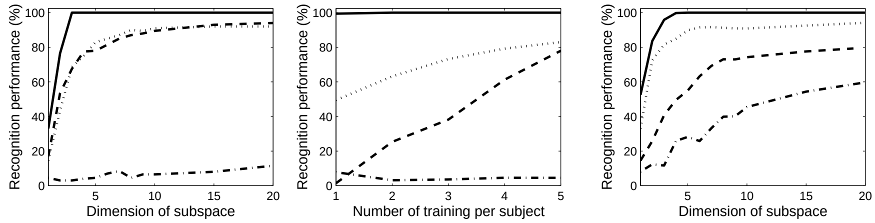
Figure 4: Example of using elastic curves to predict missing parts of edges of partially obscured objects.

and the COIL databases, where the performance of our optimal subspaces is compared with commonly used subspaces such as PCA, ICA, and FDA.

4. **Recognition of Objects Using IR and Range Sensing**: A major area of research in military target recognition is multi-modality target recognition. Advent of cheap, hand-held infrared and range sensors have enabled the use of these technologies in civilian applications also. We have investigated the use of infrared and range sensing in identifying people from their multi-modal images.

   (a) Face Recognition Using IR Images: A Bayesian approach to identifying faces from their IR facial images amounts to testing of discrete hypotheses in presence of nuisance variables such as pose, facial expression, and thermal state. We have proposed an efficient, low-level technique for hypothesis pruning, i.e. short-listing high probability subjects, from given observed image(s) [22]. (This subset can be further tested using some detailed high-level model for eventual identification). Hypothesis pruning is accomplished using wavelet decompositions (of the observed images) followed by analysis of lower-order statistics of the coefficients. Specifically, we filter infrared (IR) images using bandpass filters and model the marginal densities of the outputs via a parametric family, Bessel K-forms, that was introduced in [5]. IR images are compared using an L^2-metric computed directly from the parameters. Results from experiments on IR face identification and statistical pruning are presented in [22, 24]. Some example images of the IR face images used in the experiment are shown in Figure 7.

   Here is a tabulation of the face recognition performance using our Bessel K parametric



(a) (b) (c)

Figure 5: The performance of different linear subspaces with respect to the dimensionality and the number of training images on the ORL and COIL-20 dataset. Here solid line is for optimal subspace found using our algorithm, dashed line is for FDA, dotted line is for PCA, and dash-dotted line is for ICA. (a) The performance versus d with $k_{train} = 5$ on the ORL dataset. (b) The performance versus k_{train} with $d = 5$ on the ORL dataset. (c) The performance versus d with $k_{train} = 8$ on the COIL dataset.

models, compared with some standard techniques used in image-based face recognition.

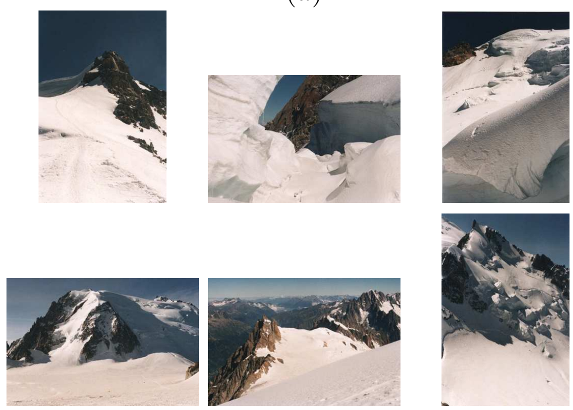
Recognition performance of PCA, ICA, and Bessel K forms

	Correct to be the closest		
Test/training ratio	Eigen faces	Independent faces	Bessel forms
1:1	90.48%	89.52%	97.14%
3:1	87.42%	88.05%	91.20%
7:1	80.21%	70.05%	83.96%
	Correct within the closest two		
Test/training ratio	Eigen faces	Independent faces	Bessel forms
1:1	94.29%	96.19%	99.05%
3:1	92.45%	91.20%	96.23%
7:1	87.70%	83.42%	91.98%

(b) **Face Recognition Using Range Images**: In this paper we consider the problem of recognizing people from their range images. The first task is to generate range images, also called height maps, of faces using observations from 3D scanners. Once the range images are generated, they need to be aligned in order to compare different range images. We perform this alignment using spatial features such as nose, bridge of the nose, etc. Aligned images are elements of a high dimensional image space. Since our technique for face recognition is statistical, we reduce the dimension of the image space using any standard linear projection such as PCA or an optimal projection found as described earlier. Probability models are imposed on the projected coefficients. Shown in Figure 8 are six examples of registered face images: top panels show images of different people and bottom panels show images of a person's face under three different facial expressions. For comparing different faces, we impose a metric on the space of coefficients. Using the Euclidean metric, we have found a reasonable success in recognizing people from their range images. Currently we are working on extending our database to include range images of hundreds of people, each with several different facial expressions. For details on this experiment, please refer to the report [7].

5. **Statistical Inferences on Certain Manifolds & Applications**: Monte Carlo (MC) methods have become an important tool for inferences in non-Gaussian and non-Euclidean settings.

(a)



(b)

Figure 6: Query examples on the retrieval dataset from the University of Washington using the learned optimal representation. Here $R = 5$. In each subfigure, the top left image is the query image and the rest are retrieved images ordered by similarity from left to right and top to bottom.

We have studied the use of MC methods in those signal/image processing scenarios where the parameter spaces are certain Riemannian manifolds (finite-dimensional Lie groups and their quotient sets). We have investigated the estimation of *means* and *variances*, of the manifold-valued parameters, using two popular sampling methods: independent and importance sampling. Using Euclidean embeddings, we specified the notions of *extrinsic and intrinsic means*, employed Monte Carlo methods (independent and importance sampling) to estimate these means, and utilized large-sample asymptotics to approximate the estimator covariances. We have used the problems in target pose estimation [4] (orthogonal groups), signal subspace estimation [19] (Grassmann manifolds) and statistical analysis of planar shapes [10] as are our motivations for this work. Asymptotic covariances are utilized to construct confidence regions, to compare estimators, and to determine the sample size for MC methods [18].

6. **Asymptotic Performance Analysis of Bayesian ATR**: We have investigated the asymptotic performance of Bayesian target recognition algorithms using deformable-template representations. Rigid CAD-models represent the underlying targets; low-dimensional matrix Lie-groups extend them to particular instances. Remote sensors observing the targets are modeled as projective transformations, converting three-dimensional scenes into random images. Bayesian target recognition corresponds to hypothesis selection in the presence of nuisance parameters; its performance is quantified as the Bayes' error. Analytical expressions for this error probability in small noise situations are derived, yielding asymptotic error rates for exponential error probability decay.

Figure 7: Example images from FSU IR face database.

For an observed image I^D, the recognition problem is to decide which target $\alpha \in \mathcal{A}$ best describes that I^D. Associate with each target $\alpha_i \in \mathcal{A}$, a hypothesis H_i which selects α_i as the best match. H_0 is the null hypothesis signifying that no target is present. A Bayesian approach is to solve a series of binary likelihood-ratio tests:

$$\frac{P(H_i|I^D)}{P(H_j|I^D)} \gtrless 1 \text{ or equivalently, } \quad L_{ij}(I^D) = \frac{p(I^D|H_i)}{p(I^D|H_j)} \gtrless \frac{P(H_j)}{P(H_i)} \equiv \nu_{ij} \; . \tag{3}$$

The likelihood of I^D given that a target α_i is present is

$$p(I^D|H_i) = \frac{1}{Z(\sigma)} \int_S \exp\{-\frac{1}{2\sigma^2} E_{\alpha_i}(s,\sigma)\} p(s|H_i) \gamma(ds) \; , \tag{4}$$

where $p(s|H_i)$ is the prior density on the parameter space S associated with the target α_i (hypothesis H_i). E_{α_i} denotes the likelihood energy for the candidate target α_i.

Under some simplifying assumptions, and assuming H_0 is the true hypothesis, the probability of selecting H_1 is now reduced to evaluating $Pr\{z > \kappa\}$ where

$$\kappa = \beta \log(\nu) - \frac{\beta}{2} \log \frac{\det(\ddot{E}_0(s_0, 0))}{\det(\ddot{E}_1(s_1, 0))} + \frac{1}{2\beta}, \quad \beta = \frac{\sigma}{\sqrt{l_1^2 + l_0^2 - 2\rho}} \; . \tag{5}$$

Theorem 1 *In the asymptotic situation that the noise standard deviation $\sigma \to 0$, the probability of type-I error (selecting H_1 when H_0 is true with parameter s_0) is given by*

$$\frac{1}{\sqrt{2\pi}\kappa} e^{-\kappa^2/2} \; , \tag{6}$$

where κ is given by (5).

For details of this result and other result relating to performance analysis in Bayesian target recognition, please refer to the paper [6].

3 List of Publications and Technical Reports

1. **List of Papers Published in Peer-Reviewed Journals**

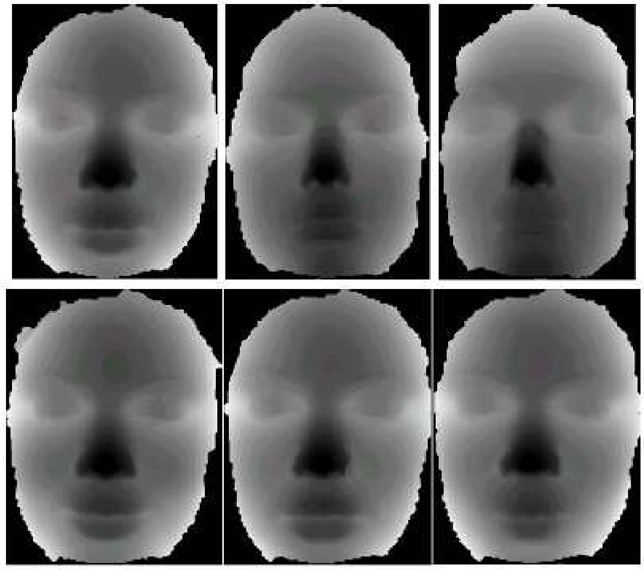


Figure 8: Top panels: face meshes (decimated for display) scanned from a 3D scanner. Bottom panels: six examples of range images of faces.

(a) A Bayesian Approach to Geometric Subspace Estimation, *IEEE Transactions on Signal Processing*, vol. 48, no. 5, pages 1390-1400, 2000. (A. Srivastava).

(b) Asymptotic Performance Analysis of Bayesian Object Recognition, *IEEE Transactions on Information Theory*, vol. 46, no. 4, pages 1658-1665, July 2000.

(c) Probability Models for Clutter in Natural Images, *IEEE Transactions of Pattern Analysis and Machine Intelligence*, vol 23, number 4, pages 424-429, April 2001. (U. Grenander and A. Srivastava)

(d) Monte Carlo Extrinsic Estimators for Manifold-Valued Parameters, special issue of *IEEE Transactions on Signal Processing*, vol. 50, no. 2, pages 299-308, February 2002. (A. Srivastava and E. Klassen)

(e) Universal Analytical Forms for Modeling Image Probabilities, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 9, pages 1200-1214, September 2002. (A. Srivastava, X. Liu, and U. Grenander)

(f) Jump-Diffusion Markov Processes on Orthogonal Groups for Object Recognition, *Journal of Statistical Planning and Inference*. vol. 103, no. 1-2, pages 15-37, April 2002. (A. Srivastava, G. Jensen, U. Grenander, and M. I. Miller).

(g) Stochastic Models for Capturing Image Probabilities, *IEEE Signal Processing Magazine*, special issue on Stochastic Methods in Image Processing, vol. 19, no. 5, pages 63-76, September 2002. (A. Srivastava)

(h) Statistical Hypothesis Pruning for Recognition of Faces in Infrared Images, *Journal of Image and Vision Computing* on Computer Vision Beyond Visual Spectrum, accepted, Septemeber 2002. (A. Srivastava and X. Liu)

(i) Interpolations with Elasticae in Euclidean Spaces, *Quarterly of Applied Mathematics*, accepted for publication, November, 2002. (W. Mio, A. Srivastava, and E. Klassen)

(j) On Advances in Statistical Modeling of Natural Images, *Journal of Mathematical Imaging and Vision*, vol. 18, no. 1, pages 17-33, 2003. (A.Srivastava, A. B. Lee, E. P. Simoncelli, and S. C. Zhu).

2. **List of Book Chapters**:

   (a) Monte-Carlo Techniques for Automated Target Recognition, chapter in *Sequential Monte Carlo Methods: Theory and Applications*, Editors: Gordon, Doucet and DeFreitas, pages 533-553, Springer, 2001. (A. Srivastava, A. D. Lanterman, U. Grenander, M. Loizeaux, and M. I. Miller)

   (b) Bayesian Automated Target Recognition, chapter in *Handbook of Video and Image Processing*, Editor: Alan Bovik, pages 869-881, 2000, Academic Press. (A. Srivastava, M. I. Miller and U. Grenander).

3. **List of Papers in Review at Peer-Reviewed Journals**

   (a) Geometric Nonlinear Filtering for Subspace Tracking, in review at *Journal of Advances in Applied Probability*, June 2000. (A. Srivastava and E. Klassen)

   (b) Models for Statistical Analysis of Range Images, submitted to *Journal of Advances in Applied Probability*, December 2001. (U. Grenander, A. Srivastava, and Curt Hesher).

   (c) Optimal Linear Representations of Images for Object Recognition, in review at *IEEE Transactions of Pattern Analysis and Pattern Recognition*, November 2002. (X. Liu and A. Srivastava).

   (d) Analysis of Planar Shapes using Geodesic Paths on Shape Spaces, in review at *IEEE Transactions on Pattern Analysis and Machine Intelligence*, revised on March 2003.

4. **Partial List of Papers published in Conference Proceedings**

   (a) Optimal Linear Representations of Images for Object Recognition, in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, Madison, WI, June 2003. (X. Liu, A. Srivastava, and K. Gallivan).

   (b) Integrated Learning of Linear Representations, in Proceedings of 2003 International Joint Conference on Neural Networks, Portland, Oregon, July 2003. (X. Liu, A. Srivastava, and D. Wang).

   (c) On Intrinsic Generalization of Low Dimensional Representations of Images for Recognition, in Proceedings of 2003 International Joint Conference on Neural Networks, Portland, Oregon, July 2003. (X. Liu and A. Srivastava)

   (d) Geometric Analysis of Continuous Planar Shapes, in Proceedings of Fourth International Workshop on Energy Minimization Methods in Computer Vision and Pattern Recognition, Lisbon, Portugal, July 2003. (A. Srivastava, E. Klassen, W. Mio and S. Joshi).

   (e) Stochastic Search for Optimal Linear Representations of Images on Grassmann Manifolds, in Proceedings of Fourth International Workshop on Energy Minimization Methods in Computer Vision and Pattern Recognition, Lisbon, Portugal, July 2003. (X. Liu and A. Srivastava).

   (f) Geometric Analysis of Planar Shapes Using Geodesic Paths, in Proceedings of 35th Annual Asilomar Conference on Signals, Systems, and Computing, Asilomar, CA, November 2002. (A. Srivastava and E. Klassen).

(g) Spaces and Subspaces of Images for Recognition, in Proceedings of the International Conference on Image Processing, in press, Rochester, 2002. (with X. Liu).

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(k) Image Segmentation using Local Histograms, in Proceedings of IEEE International Conference on Image Processing, volume 1, pages 70-73, Thessaloniki, Greece, October 2001. (with X. Liu and D. Wang).

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(o) Bayesian Filtering for Tracking Pose and Location of Rigid Targets, in Proceedings SPIE, volume 4052, pages 160-171, Signal Processing, Sensor Fusion, and Target Recognition IX, Ivan Kadar (Ed), Orlando, FL, April 2000.

(p) A nonlinear Filtering Method for Geometric Subspace Tracking, in Proceedings of IEEE Sensor Array and Multichannel Processing workshop, Cambridge, MA, March 2000

The research performed under this contract was also presented at several meetings including the Royal Statistical Society's annual meeting in Glasgow, Scotland, AFOSR/AFRL Nonlinear filtering/Tracking workshop in Dayton, Joint Statistical Meeting in Atlanta, International Conference on Pattern Recognition in Washington, NSF Workshop on Pattern Classification in Ann Arbor, and UFL Winter workshop on Classification in Gainesville.

4 Scientific Personnel Supported

This funding supported partial summer salary of the PI for three summers (1999, 2000, and 2001). In addition, three graduate students, Wenji Pu, Brian Thomasson and Evgenia Rubenshtein, were also supported on a half RA, half TA basis. Brian Thomasson finished his MS degree and is currently an instructor of Statistics at North Florida Community College. Evegenia is currently working on her phd in the area of statistical mideling of images.

While the PI was supported by this grant, he directed Lt. Col. Mick Smith (of US Army) on his phd dissertation titled *Bayesian Sensor Fusion for Inferences from Multi-Modal Data*. Motivated by the problems facing Army's NVL, Mick has developed new statistical models for sensors such as human scout and seismic recorder, and combined them with existing models for IR camera and acoustic sensing, to produce a framework for unified inference. He is expected to finish his phd degree in July 2003 and will join US Military Academy at Westpoint as an instructor in Statistics.

This research was performed in collaboration with several researchers, none of whom was supported by this grant. Profs. Xiuwen Liu of Department of Computer Science and Ulf Grenander of Brown University played an integral part in development of Bessel K forms, and their applications. Prof. Liu also led the project on finding optimal linear representations of images for object recognition and image retrieval. We collaborated with Profs. Eric Klassen and Washigton Mio, both of Department of Mathematics, on the statistical analysis of planar shapes and elastic curves. Prof Klassen also was instrumental in development of statistical inferences on nonlinear manifolds.

5 Report of Inventions

None.

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